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Employment of PSO algorithm to improve the neural network technique for radial distribution system state estimation

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Abstract

This study presented a new hybrid algorithm to improve the state estimation (SE) of radial distribution power systems (PSs). The proposed particle swarm optimization–neural network (PSO–NN) algorithm constructed an independent and fast monitoring system with high accuracy that can detect abnormal conditions or failures in a PS. In this study, PSO was adopted to determine the appropriate weights of the NN model. The speed and accuracy of PSO with the NN model were evaluated in the SE of power system networks (PSNs). The information obtained through SE was used to enhance the operations and customer service delivery in terms of energy consumption and power quality in PSNs. Capacitor banks were installed to reduce the losses and improve the voltage profiles. The PSO–NN algorithm was assessed on IEEE (9, 33, and 69) bus standards. Simulation results proved that the new technique can be tested on any distribution network because of its accurate and efficient SE. Results indicated that the PSO–NN algorithm had better performance than the phasor measurement units.

Keywords

RDPS, RDPS, PSO, Neural network, Hybrid algorithm, State estimation, Monitoring system, Optimization methods, PMU.

Nomenclatures

SE state estimation
PS power system
PSN power system networks
PSO–NN particle swarm optimization–neural network
DPN distribution power network
RDPSNs radial distribution power system networks
DMS distribution management system
GTP graph theoretic procedure algorithm
DSSE distribution system state estimation model
WLS weighted least square
WLAV weighted least absolute value
PMUs phasor measurement units
ANN artificial neural network
EMS energy management system

Energy management systems (EMSs) have become obsolete as control frameworks due to the expansion of interconnected electric power frameworks and the multifaceted nature of intensity framework structures (Lu et al., 1993; Gastoni et al., 2004; Pajic and Clements, 2005). State estimation (SE) performs an essential job in EMSs and provides a dependable and predictable framework. This condition requires the improvement of power system (PS) operations. Energy transmission from a small number of nodes (substations) to a multitude of consumers is performed by the electric distribution system. Future system networks of electric power distribution will be 'smart,' more efficient, better secured, and capable of distributing more reliable and affordable electric power than today's system network (Smart Grid, 2008; Husham and Ahmed, 2018). The magnitudes and angles of branch current or system node voltages often define the SE of a distribution PS. A system of nonlinear equations is formed with the available information about the reactive and real power and their states. PSSE is defined as 'a data processing algorithm that converts redundant meter readings and other available information into an SE of an electric PS.' As shown in Figure 1, ample measurement redundancies in the transmission network has allowed system observation and processing of bad data in SE after more than four decades of development.

A review of important algorithms and DSSE requireiments in distribution management systems is provided in the study of Jako (2009). DSSE's future as part of the vision for a smart grid and as an emerging technique is identified. Two SE techniques that use compressed power measurements are presented in the study of Anggoro and Chan (2017). The primary computational complexities of the two methods are discussed. Direct and indirect SE approaches can accurately estimate voltage states by randomly projecting only half of the available power information, and they have similar performance with the same complexity order. WLS and WLAV methods of power SE are described in the study of Shafiul et al. (2014). The proposed estimation method can still estimate the PS state because it has fewer variables than WLAV and a wider performance range than WLS although the system is unobservable. A complete formula is provided for single and three-phase DSSE optimization problems on the basis of the system voltage drop formula and system quasi-symmetric matrix, as presented in the study of Syed et al. (2017). DSSE is suitable for large-scale radial-exploited distribution feeders by removing interconnecting nodes with null-injected reactive and active powers, as proposed in the study of Hornik et al. (1989).

The artificial neural network (ANN) is fed with adopted phase angles and voltage magnitudes as inputs. This process greatly improves the precision of load active power margin estimation for the New England 39-bus system. Phasor measurement units (PMUs) proposed in the study of Seyed and Mohammad (2014) can provide phase angles and voltage magnitudes for real-time applications. In addition to normal steady-state conditions, the ANN-based system can estimate voltage stability margins under different possibilities. To achieve a good ANN performance, the ANN algorithm is used in this work as a mapping tool for estimating the available voltages and margin angles of the system. Feed forward networks can approximate any measurable function to the desired accuracy level (Chakrabarti and Jeyasurya, 2004; Zhou et al., 2010; Paulo et al., 2013; Paulo et al., 2015; Ghassan et al., 2018). This advantage is tackled in this study. The proposed ANN approach is compact and efficient because it is fed with the input features of the post-power flow. Installing PMUs at every node and connecting them to fast and reliable telecommunication channels to gather the required inputs are inefficient. A limited number of PMUs should be placed at important locations. Thus, a suboptimal search method is proposed for the placement of PMUs. The placement of PMUs for detecting bad data is proposed in the studies of Popovic et al. (1998) and Husham (2016). This study indicates that system observability is improved by critically eradicating measurements when the number of strategically placed PMUs is minimum. This process enhances bad data detection. The concept of robust distances was presented by Chen and Abur (2008) to

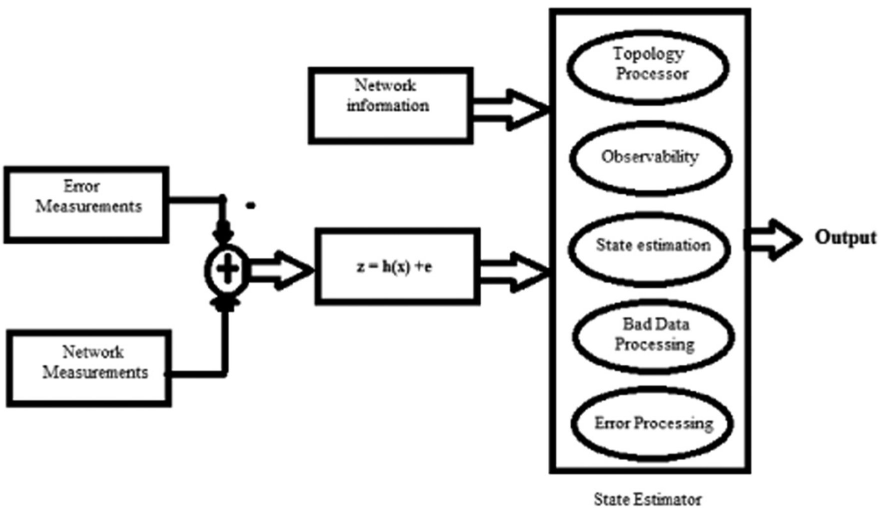

Figure 1: General scheme of state estimation (Husham and Ahmed, 2018).

detect the difference between bad and good leverage measurements. They posited that a robust estimator performs better than a WLS estimator with the presence of bad leverage data point and bad data.

This study presented a new hybrid algorithm that uses PMUs to evaluate the SE of radial distribution in PSs. The proposed hybrid algorithm is a combination of particle swarm optimization (PSO) and NN model in which PSO was used to determine the appropriate weights of the NN model. The speed and accuracy of PSO and ANN were evaluated in the SE of power system networks (PSNs). The PSO–NN algorithm was tested on three radial distribution PSNs (RDPSNs) of IEEE (9, 33, and 69) buses. The networks were designed using MATLAB/PSAT package. The hybrid algorithm code was developed using a MATLAB program. Capacitor banks were installed as VAR compensators to reduce the power losses and improve the voltage profiles of RDPSNs.

Problem formulation

Conventional SE is the same as the objective function of distribution SE, which is expressed as follows:

$$\min J(x) = \sum_{i=1}^{m} w_i \left(z_i - h_i(x)\right)^2, \tag{1}$$

where h_i is the state equation of measurement variable i; w_i the weighting factor of measurement variable i; x the state variable including the loads and C outputs; z_i the measurement value of measurement variable i.

Where:

$$\bar{x} = \left[v_i, \delta_i, P_{gi}, Q_{gi}\right]. \tag{2}$$

The difference between the measured and calculated state variables is minimized by using this function. One of the state variables is used as a load value at each section rather than a voltage utilized by conventional state estimators. Therefore, the reactive and active state power values are used as state variables. The input values V and δ are also used as state variables. In the study of Narvaez and Grijalva (2008), the state variables are obtained among the boundaries.

Constraints

The constraints of the objective function are defined as follows:

$$x_{j,\min} \leqslant x_j \leqslant x_{j,\max}, \tag{3}$$

where $x_{j,\max}$ is the maximum value of the state variable j; $x_{j,\min}$ the minimum value of the state variable j.

$$0 \leqslant Q_c^i \leqslant Q_{c,\max}^i, \quad i = 1, 2, \ldots, N_c, \tag{4}$$

where Q_c^i is the reactive power of ith capacitor bank; $Q_{c,\max}^i$ the maximum reactive power of ith capacitor bank; N_c the number of capacitors bank installed on feeders.

$$v_{\min,i}^{PH} \leqslant v_i^{PH} \leqslant v_{\max,i}^{PH}, \tag{5}$$

$$\delta_{\min,i}^{PH} \leqslant \delta_i^{PH} \leqslant \delta_{\max,i}^{PH}, \tag{6}$$

where v_i^{PH}, $v_{\min,i}^{PH}$, $v_{\max,i}^{PH}$ are the state variable of voltages minimum value and maximum voltages values; and δ_i^{PH}, $\delta_{\min,i}^{PH}$, $\delta_{\max,i}^{PH}$ the state variable of bus voltage angles, minimum value, and maximum bus voltage angles values.

The ratio of the target section to the total load of the target network and the total power inputted into the target network are used to calculate the center value of the bound at each load. The average input is the center value of the bound of each variable. Fast power flow distribution is utilized to calculate the current and voltage (Shigenori et al., 2001).

PMUs and capacitor location

A PMU can measure the current phasors of some or all of the lines connected to the installed bus and the voltage phasors of the installed bus. Efficient placement strategies (benefits derived from PMUs) should be applied to justify the costs of bringing the measurement system up to date. PMU placement methods are facing a huge challenge from the increasing dependence on renewable energy sources that are constantly added to modern distribution grids (Fukuyama et al., 1996).

A distribution grid is converted to an active system and its power path flow is changed by distribution generators. Literature review of papers (Manousakis et al., 2011; Ren and Jordan, 2018) published in the past addressed PMU placements in their classification of PMU placement problems on the basis of the algorithms and methods utilized to determine the difficulty of selecting the location and ideal number of installed PMUs. Graph theoretic procedure (GTP), integer programming, PSO, and generic algorithm methods have different constraints and different requirements for PMU installation objectives, which can be used to achieve different goals in different cases.

Rules that can be applied to PMU systems to make them observable are as follows:

- Rule 1: the current phasor and bus voltage of all incident branches of installed PMU at a bus are all known.
- Rule 2: the voltage phasor at the other end of one end of a branch can be obtained using Ohm's law when the current and voltage phasor at the other end of the branch are known.
- Rule 3: the current phasor through a branch can be calculated when the voltage phasors at two ends of the branch are known, as shown in Figure 2. In this study, a GTP algorithm was utilized to determine the location of PMUs. This process was conducted to show the observability on the basis of the topology and to ensure full observability on the optimal placement of PMUs.

A simple approach for determining the locations and sizes of capacitor banks in RD feeders was presented in this study. In this approach, the total reactive loads and total reactive losses in all sections of the feeders were the same as the amount of required compensation for any feeder (Manousakis et al., 2012).

We installed capacitor banks on a bus through trial and error method to minimize power losses and improve voltage profiles. In the distribution network, the compensation of reactive power is a vital issue. Transformers, converters, and induction motors are combined to consume reactive power (More and Jadhav, 2013). A reasonable amount of reactive power is not transmitted through the network because the voltage drop and energy losses are increased. Thus, reactive power should be generated close to its consumers (Huang et al., 2014; Mohamed et al.). Figure 3 illustrates the effect of reactive power compensation.

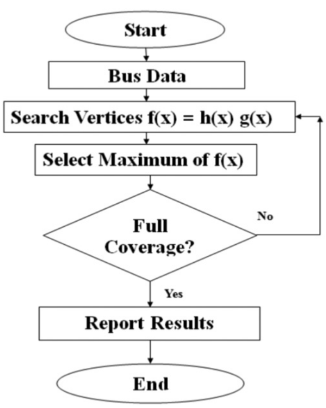

Figure 2: Flow chart for the placement of PMUs for network observability.

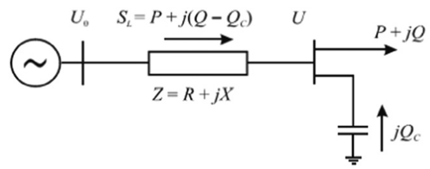

Figure 3: Reactive power compensation principle (Husham and Ahmed, 2018).

Compensating devise Q_c is connected to the consumer terminals, and the power delivered through a distribution line is as follows:

$$S_L = P + j\left(Q - Q_c\right), \tag{7}$$

where S_L is the power delivered; P the real power; Q and Q_c the reactive power and reactive power compensator.

Hybrid PSO–NN algorithm

Each NN in PSO–NN consists of its velocity and network position. The weight of the NN (W) is related to the network position. The network's velocity (ΔW) is equivalent to updating the NN's weight. PSO's main role in the NN is to attain the best set of weights (particle positions) where numerous particles are aiming for the best solution.

A PS is composed of numerous particles. Each particle monitors its own position, best position, velocity, best fitness, current fitness, and the particles nearby. To operate the NN successfully, the position vector should match the weight vector of the network. The fitness value should match the forward transmission through the network. The particle's new solutions are guided by using its best neighbor and global best particle. The particle's position serves as the answer at the end (Hamada et al., 2008). The PSO's main task in the NN is to secure the best set of weights in a situation where numerous NNs compete for the best solutions. The velocity vector is given by the following equation:

$$v_i^{k+1} = wv_i^k + c_1 r_1\left(P_{besti}^k - X_i^k\right) + c_2 r_2\left(g_{besti}^k - X_i^k\right). \tag{8}$$

In each iteration the position of each particle is updated by using the velocity vector of the following equation:

$$X_i^{k+1} = X_i^k + V_i^{k+1}, \tag{9}$$

where X_i^k is the particle position at (k) iteration; X_i^{k+1} the particle position at ($k+1$) iteration; V_i^k the particle velocity of at (k) iteration; V_i^{k+1} the particle velocity at ($k+1$) iteration; w the weight parameter; r_1 and r_2 the random number; c_1 and c_2 the learning factors [0, 1].

The development of the PSO–NN model with its angle and voltage magnitude is expressed as follows:

1. A population of NNs with various initial weights was assembled for the PSO–NN.
2. For every NN (particle), an iteration of the training data set was conducted, and the sum of squared errors was calculated.
3. All the errors of NNs were compared to find the best NN in the neighborhood.
4. The weights of the network were recorded, and Step 6 was performed when one of the networks exceeded the required minimum errors. Otherwise, Step 5 was performed.
5. The PSO algorithm was applied for each NN to update its position, that is, its velocity vector (ΔW) and weight (w).
6. The set error goal was obtained from the trained PSO–NN.
7. The testing pattern was applied to evaluate the performance of the trained PSO–NN.

The PSO–ANN model aimed to estimate bus voltage and bus voltage angles.

Simulation results and discussion

A distribution system is characterized with short lines that have high R/X ratios and systems that are unbalanced. This system experiences more losses than a transmission network. An RDS normally spreads over a large area (Husham et al., 2018). This condition makes many customers' domestic loads difficult to monitor and measure. The network's observability and state estimator's capability to provide realistic estimates are also hampered. This serious challenge can be tackled by using PMUs. This study compared the results of the proposed hybrid algorithm (PSO–NN) with the results of PMUs.

In this study, a new algorithm was tested on PSNs as an observational system to determine the increase and decrease of bus voltage and their angles. Some differences were observed between the values because the networks were monitored rather than performing aggregate analysis, as shown in Figures 7, 8, and 10.

The proposed PSO–NN algorithm was designed on MATLAB. RPDSN IEEE (9, 33, and 69) bus standards were developed and simulated using a MATLAB/PSAT toolbox. PMUs were applied on the distribution networks by using the toolbox. Then, a GTP algorithm was adopted to find the PMU's location. The capacitor bank's size and location were determined through trial and error method. For each test, the number of capacitors and PMUs varied. As shown in Table 1, the measurements had low MSE.

The proposed PSO–NN algorithm and its installed PMU (Manousakis et al., 2012) were evaluated on three tests.

Test 1: IEEE 9-bus RDPSN

A PSAT package is used to mount a PMU on the IEEE 9-bus radial distribution network that has been designed. Two capacitor banks with sizes of 0.045 and 0.05 p.u are installed on buses 4 and 7, respectively, to improve bus voltage. Then, four PMUs are fixed on buses 2, 4, 6 and 8.

As shown in Figures 4 and 5, the results of the PSO–NN algorithm reveal that the state estimator has a good validation. As shown in Table 1, the input

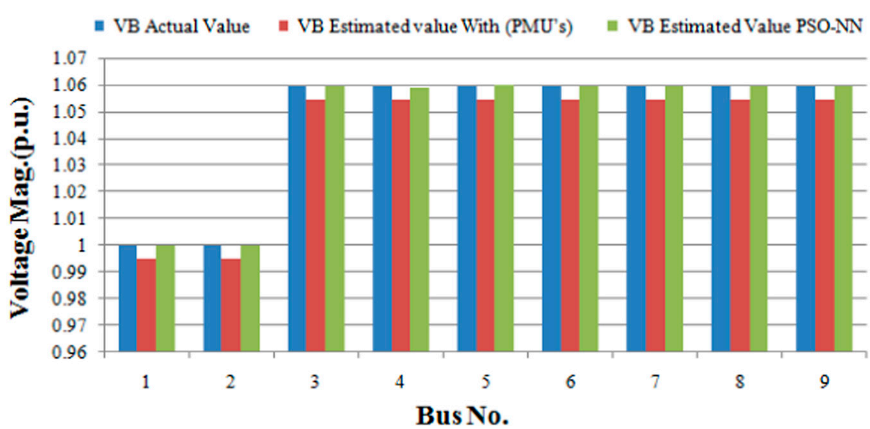

Figure 4: Voltage bus magnitude (actual, estimated PMU, estimated PSO–NN) of IEEE 9-bus RDS.

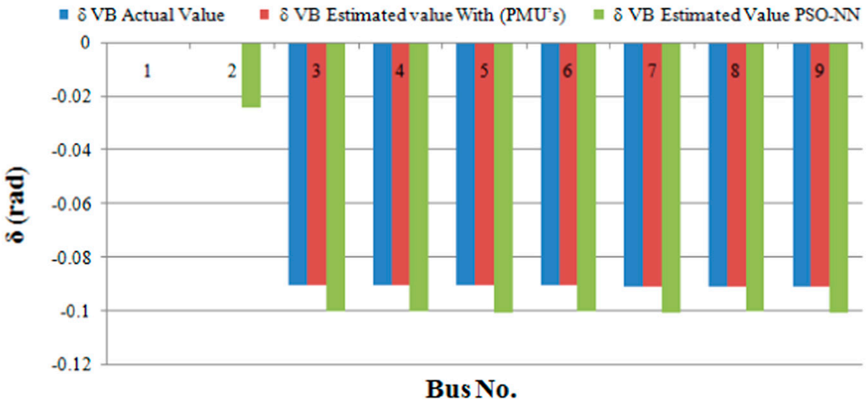

Figure 5: Voltage bus angle (actual, estimated PMU, estimated PSO–NN) of IEEE 9-bus RDS.

Table 1. MSE for voltage magnitudes and angle values in each test.

Test	VB MSE	δ MSE
IEEE 9	6e–08	4e–07
IEEE 33	2.5e–07	4e–07
IEEE 69	1.43e–10	5.5e–09

value is consistent with the output (target) with only a small error margin. $R=0.99996$ and $R=0.99991$ are the regressions for bus voltage and δ bus voltage, respectively, as illustrated in Figure 6.

Test 2: IEEE 33-bus RDPSN

The IEEE 33-bus network is designed using the PSAT package. Four capacitor banks, each with a size of 1 p.u, are mounted on buses 18, 20, 24, and 29. In total, 14 PMUs are fitted on buses 1, 11, 13, 15, 17, 19, 21, 24, 28, 3, 30, 32, 6, and 9. The PSO–NN algorithm used obtains a good correspondence between the input and output (target) with only a minor error, as shown in Table 1. Figures 7 and 8 show a full comparison between the actual and estimated values. $R=0.98354$ and $R=0.98606$ are the regressions for bus voltage and δ bus voltage, respectively, as shown in Figure 9.

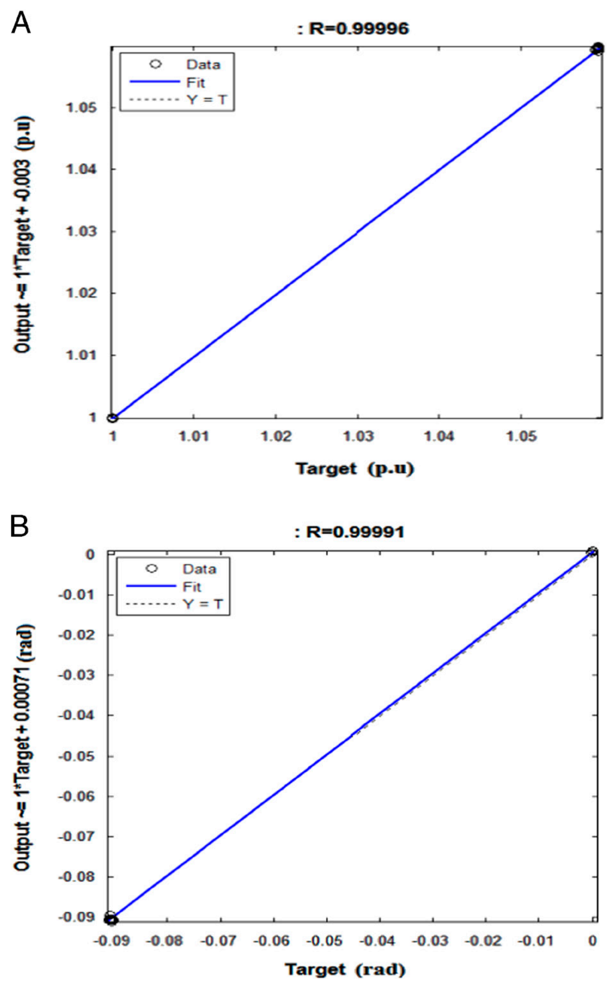

Figure 6: Regression plots of IEEE 9 bus: (A) bus voltage magnitudes; and (B) angle bus voltage values.

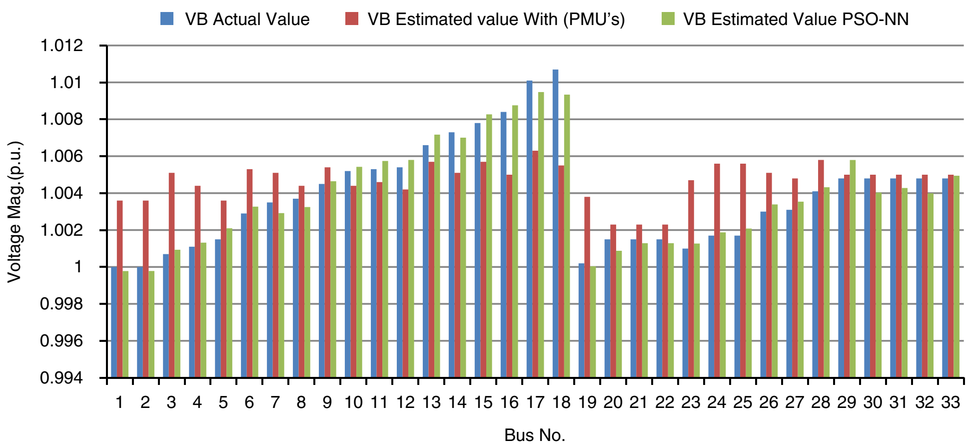

Figure 7: Voltage bus magnitude (actual, estimated PMU, estimated PSO–NN) of IEEE 33-bus RDS.

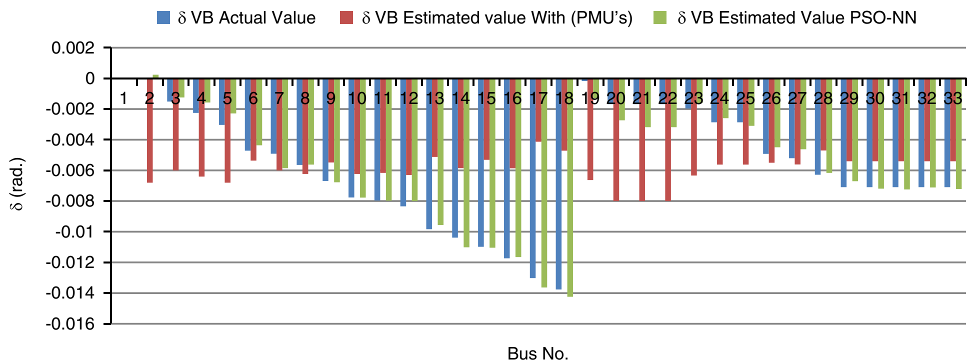

Figure 8: Voltage bus angle (actual, estimated PMU, estimated PSO–NN) of IEEE 33-bus RDS.

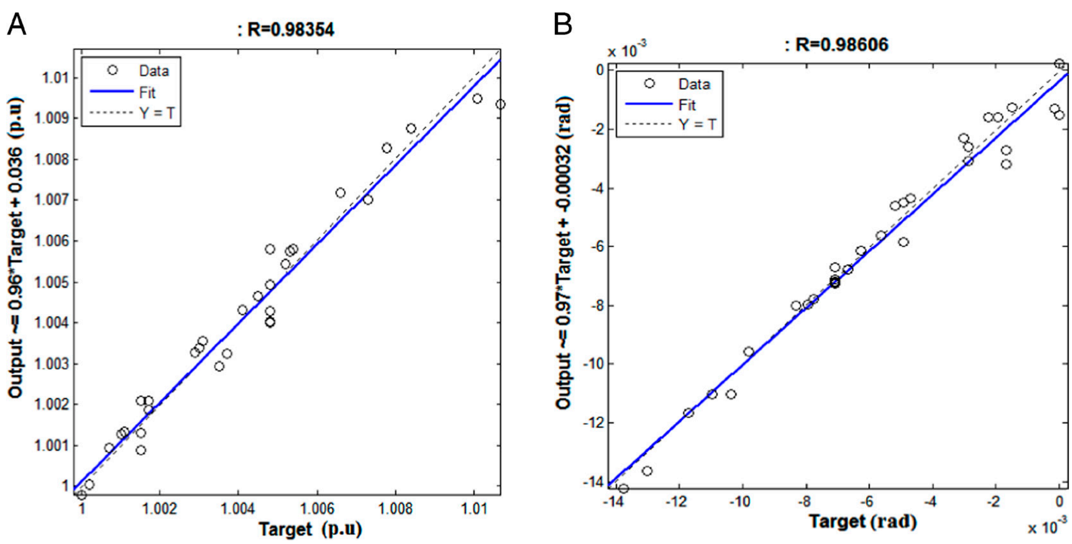

Figure 9: Regression plots of IEEE 34 bus: (A) bus voltage magnitudes; and (B) angle bus voltage values.

Test 3: IEEE 69-bus RDPSN

Four capacitor banks are installed on buses (24, 45, 49, and 63), each with a size of 0.55 p.u to improve the voltage profiles. In total, 27 PMUs are installed on buses 12, 15, 17, 19, 21, 23, 26, 3, 32, 34, 38, 40, 42, 45, 49, 5, 51, 54, 58, 60, 62, 64, 66, 69, 7, 69, and 9 to ensure network observability. As shown in Figures 10 and 11, similar results were obtained between the input and target when the PSO–NN algorithm was tested in the network. As presented in Table 1, errors appeared in the results. As shown in Figure 12, $R = 0.99934$ and $R = 0.99583$ were the regressions for the bus voltage and δ bus voltage, respectively.

As previously mentioned, the simulation results proved that the hybrid PSO–NN algorithm can be tested on any distribution network because of its accurate and efficient SE of the input values and target.

Conclusions

A new algorithm was developed in this study for the SE of angle bus voltage and voltage magnitude of RDPSNs. Voltage was a good predictor of the

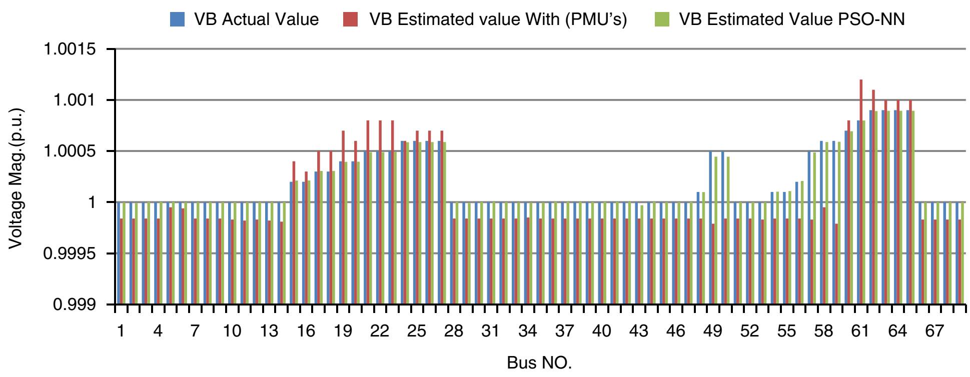

Figure 10: Voltage bus magnitude (actual, estimated PMU, estimated PSO–NN) of IEEE 69-bus RDS.

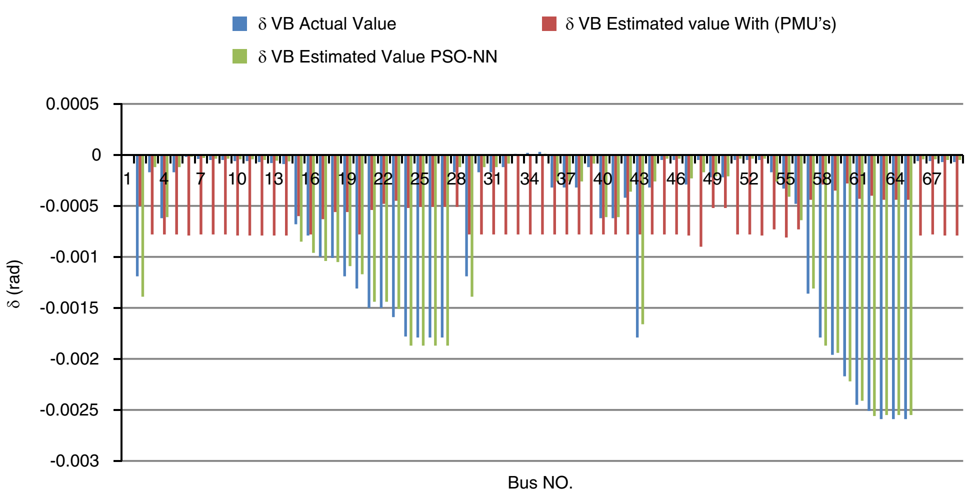

Figure 11: Voltage bus angle (actual, estimated PMU, estimated PSO–NN) of IEEE 69-bus RDS.

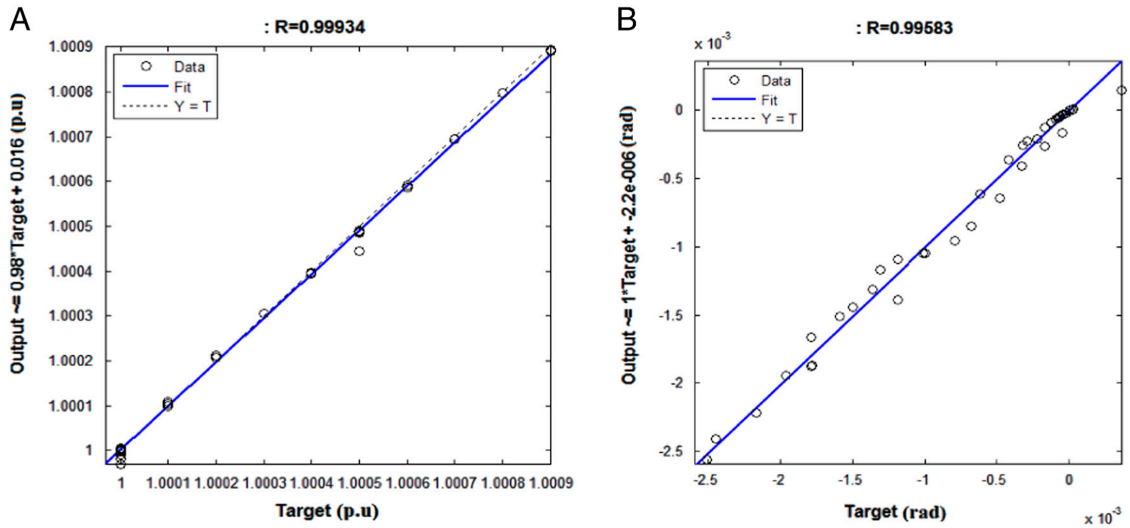

Figure 12: Regression plots of IEEE 69-bus: (A) bus voltage magnitudes; and (B) angle bus voltage values.

proximity to voltage collapse, and phase angle was a good predictor of power flow. Capacitor banks were installed to enhance the voltage profiles. PMUs were installed to make the networks observable. Results indicated that redundancy occurred and the accuracy of the estimated states improved when synchronized PMUs were added into the measurement sets. Three distribution networks were used in the SE of IEEE (9, 33, and 69) buses. The simulation results showed that the proposed algorithm was accurate and fast and only required few variables. A small MSE difference was observed between the target output and the output obtained by utilizing PMUs and PSO–NN, as shown in the regression plots for each network. The target output was represented by a dotted line. MATLAB software and PSAT package were used to obtain the results. The SE problem was transformed to a constrained problem and solved using the PSO–NN algorithm. The effectiveness of the proposed method was confirmed by the simulation results.

Literature Cited

Anggoro, P. and Chan, N. L. 2017. A review on distribution system state estimation. *IEEE Transactions on Power Systems* 32(5): 3875–3883, doi: 10.1109/TPWRS.2016.2632156.

Chakrabarti, S. and Jeyasurya, B. 2004. On-line voltage stability monitoring using artificial neural network. Proceedings of Large Engineering Systems Conference on Power Engineering (LESCOPE-04), July 28–30, 71–75, doi: 10.1109/LESCPE.2004.1356271.

Chen, J. and Abur, A. 2008. Discussion on placement of PMUs to enable bad data detection in state estimation. *IEEE Transactions on Power Systems* 23(2): 817–817, doi: 10.1109/TPWRS.2008.920736.

Fukuyama, Y., Nakanishi, Y. and Hsaio, D. C. 1996. Parallel power flow calculation in electric distribution networks. IEEE International Symposium on Circuits and Systems, Circuits and Systems Connecting the World, ISCAS 96, Vol. 1, Atlanta, GA, pp. 669–672, doi: 10.1109/ISCAS.1996.540036.

Gastoni, S., Granelli, G. and Montagna, M. 2004. Robust state estimation procedure based on the maximum agreement between measurements. *IEEE Transactions on Power Systems* 19: 2038–2043, doi: 10.1109/TPWRS.2004.836190.

Ghassan, A. S., Husham, I. H. and Mohamed, S. H. 2018. Enhancement the dynamic stability of the Iraq's power station using PID controller optimized by FA and PSO based on different objective functions. *Elektrotehniški Vestnik* 85: 42–48.

Hamada, M. M., Mohamed, A. A. W., Abou-Hashema, M. E.-S. and Husam, A. R. 2008. A proposed strategy for capacitor allocation in radial distribution feeders. 12th International Middle East Power Systems Conference, March 12–15, doi: 10.1109/MEPCON.2008.4562320.

Hornik, K., Stinchcombe, M. and White, H. 1989. Multilayer feed forward networks are universal approximates. *Neural Networks* 2: 359–366, available at: http://dx.doi.org/10.1016/0893-6080(89)90020-8.

Huang, L., Sun, Y. Z., Xu, J., Gao, W. Z., Zhang, J. and Wu, Z. P. 2014. Optimal PMU placement considering controlled islanding of power system. *IEEE Transactions on Power Systems* 29(2): 742–755, doi: 10.1109/TPWRS.2013.2285578.

Husham, I. H. 2016. Neural network controller based Dstatcom for voltage sag mitigation and power quality issue. *International Journal of Engineering and Technology* 8(1): 405–420.

Husham, I. H. and Ahmed, M. G. 2018. A hybrid model for state estimation prediction composed of neural network and PSO algorithm for Iraqi national super grid system. First International Scientific Conference of Engineering Sciences – 3rd Scientific Conference of Engineering Science (ISCES), 50–55, doi: 10.1109/ISCES.2018.8340527.

Husham, I. H., Ghassan, A. S. and Mohammed, S. H. 2018. Phase measurement units based FACT's devices for the improvement of power systems networks controllability. *International Journal of Electrical and Computer Engineering* 8: 888–899, doi: 10.11591/ijece.v8i2.

Jako, K. 2009. Monitoring of electrical distribution network operation. thesis on Power Engineering, Electrical Engineering, Mining Engineering D37, Tallinn University of Technology, Tallinn Estonia.

Lu, C. N., Leou, R. C., Cheng, C. L. and Rai, T. S. 1993. Modeling multiple injection bus in power system state estimation. *IEE Proceedings GTD* 140(6): 455–461, doi: 10.1049/ip-c.1993.0066.

Manousakis, N. M., Korres, G. N. and Georgilakis, P. S. 2011. Optimal placement of phasor measurement units: a literature review. *International Conference on Intelligent System Applications to Power Systems*, Hersonissos, pp. 1–6, doi: 10.1109/ISAP.2011.6082183.

Manousakis, N. M., Korres, G. N. and Georgilakis, P. S. 2012. Taxonomy of PMU placement methodologies. *IEEE Transactions on Power Systems* 27(2): 1070–1077, doi: 10.1109/TPWRS.2011.2179816.

Mohamed, M. H., Mohamed, A. A. W., Abou-Hashema, M. E.-S. and Husam, A. R. 2009. A new approach for capacitor allocation in radial distribution feeders. *Online Journal on Electronics and Electrical Engineering* 1(1): 24–29, doi: 10.1016/j.procs.2015.10.039.

More, K. K. and Jadhav, H. T. 2013. A literature review on optimal placement of phasor measurement units. Power, Energy and Control (ICPEC), 6–8, February, 220–224, doi: 10.1109/ICPEC.2013.6527654.

Narvaez, A. and Grijalva, S. 2008. Robust state estimator applied to the Ecuadorian electric power system. IEEE/PES Transmission and Distribution Conference and Exposition: Latin America, 1–6, doi: 10.1109/TDC-LA.2008.4641855.

Pajic, S. and Clements, K. A. 2005. Power system state estimation via globally convergent methods. *IEEE Transactions on Power Systems* 20: 1683–1689, doi: 10.1109/PTC.2003.1304124.

Paulo, M. D., Jesus, O. D. and Rojas Quintana, A. A. 2015. Distribution system state estimation model using a reduced quasi-symmetric impedance matrix. *IEEE Transactions on Power Systems* 30(6): 2856–2866, doi: 10.1109/TPWRS.2014.2374537.

Paulo, M. D., Jesus, O. D., Manuel, A. and Yusta, J. 2013. Distribution power flow method based on a real quasi-symmetric matrix. *Electric Power Systems Research* 95(2): 148–159, available at: https://doi.org/10.1016/j.epsr.2012.08.011.

Popovic, D., Kukolj, D. and Kulic, F. 1998. Monitoring and assessment of voltage stability margins using artificial neural networks with a reduced input set. *IEEE Proceedings – Generation, Transmission, Distribution* 145(4): 355–362, doi: 10.1049/ip-gtd:19981977.

Ren, Z. S. S. and Jordan, R. C. O. 2018. Distribution system state estimator using SCADA and μPMU measurements. 2018 IEEE Innovative Smart Grid Technologies – Asia (ISGT Asia), pp. 558–562, doi: 10.1109/ISGT-Asia.2018.8467853.

Seyed, M. M. and Mohammad, R. N. 2014. Power system state estimation with weighted linear least square. *International Journal of Electrical and Computer Engineering* 4(2): 169–178.

Shafiul, A. S. M., Balasubramaniam, N. and Anil, P. 2014. Distribution grid state estimation from compressed measurements. *IEEE Transactions on Smart Grid* 5(4): 1631–1642, doi: 10.1109/TSG.2013.2296534.

Shigenori, N., Yoshikazu, F., Takamu, G. and Toshiki, Y. 2001. Practical distribution state estimation using hybrid particle swarm optimization. Proceedings of IEEE Power Engineering Society Winter Meeting Columbus, OH, 2: 815–820, doi: 10.1109/PESW.2001.916969.

Smart Grid 2008. An introduction, available: https://www.smartgrid.gov/files/sg_introduction.pdf.

Syed, M. A., Ankur, G., Dinesh, K. C. and Saikat, C. 2017. Voltage stability monitoring of power systems using reduced network and artificial neural network. *Electrical Power and Energy Systems* 87: 43–51, doi: 10.1016/j.ijepes.2016.11.008.

Zhou, D. Q., Annakkage, U. D. and Rajapakse, A. D. 2010. Online monitoring of voltage stability margin using an artificial neural network. *IEEE Transactions on Power Systems* 25(3): 1566–1574, doi: 10.1109/TPWRS.2009.2038059.